Brain Computer Interaction (BCI)

6/1/22

→ Movie - Brain storm

→ Transcendence.

Unit-1 - Introduction to Brain CI
Unit-2 - Introduction to Basic Neuroscience
Unit-3 - Modelling & Recoding of Brain Signals
Unit-4 - Signal processing
Unit-5 : Signal Analysis using ML - Approaches
Unit-6 : BCI Applications.

— Mid, End, Quizzes, projects [Matlab or Python]

→ 1875 > Richard carton.
Electrical impulses from a living brain of rabbit and monkey were recorded

EEG - Electro Encephalo graphing.
It is a test that detects electrical activity in your brain

Challenges :-

→ Usability.

→ Hardware

→ Signal processing.

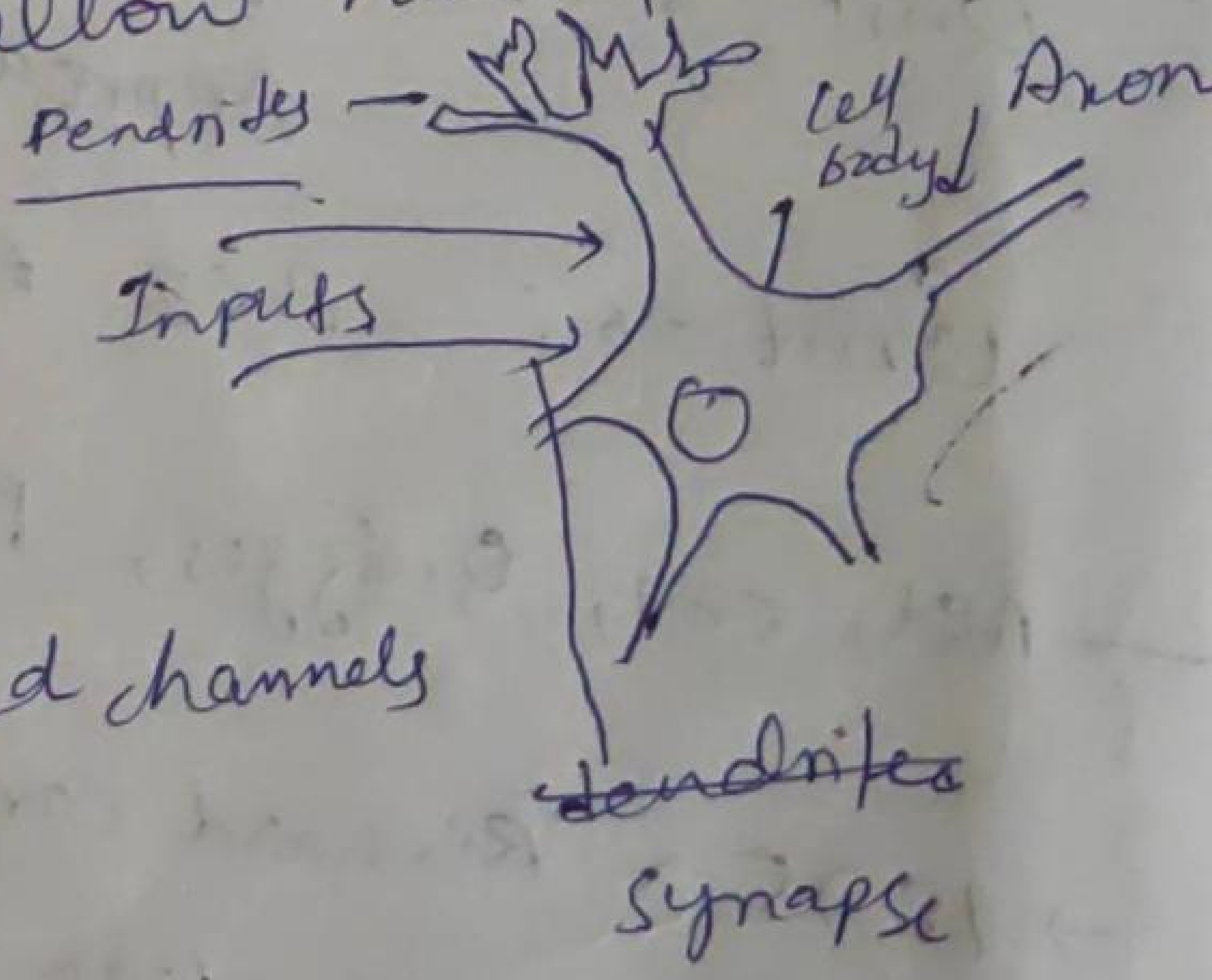
→ System Integration

→ Cost.

13/1/22

27/1/22

→ Gated channels allow neural signaling



→ Inputs from other neurons

→ chemically gated channels (at "synapses")

→ Changes in local membrane potential. [Exchange of ions - cations (+ve) [anions] (-)

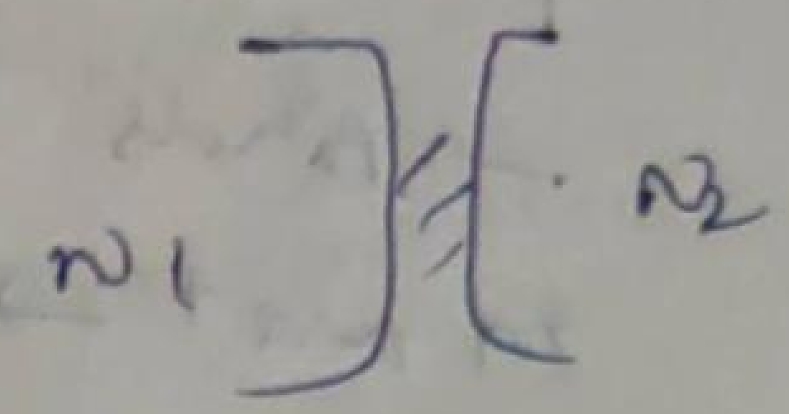
→ Depolarization (positive change in voltage)
Hyperpolarization (negative change in volta

→ Each neuron maintains a potential diff across its membrane

→ Axions covered by myelin, white sheath that boosts the propogation of spike.

Synapse –

→ Typically chemical.



→ Gap or cleft between axon of one neuron (∴ presynaptic neuron) and dendrite of another neuron (post synaptic neuron)

→ Action potential arrives from a presynaptic neuron, release of chemicals known as neurotransmitters into synaptic cleft

→ Binds to receptors (ionic channels) on post synaptic neuron & opens its channels

→ Excitatory synapse cause a momentary increase in local membrane potential of postsynaptic cell.

→ Increase is called Excitatory post synaptic potential (EPSP)

→ Decrease is Inhibitory postsynaptic potential (IPSP)

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Depolarization — EPSP → Increase in the
Hyperpolarization → IPSP → Decrease in the

→ Input spike → Neurotransmitter release.
→ Binds to Na^+ channels → Increase
in Na^+ → EPSP.

Long-term Depression or LTD :-

→ Decrease in strength of a synaptic connection caused.

→ Observed in cerebellum & other brain areas.

LTP (Long Term Potentiation) → Increase

Spike Timing dependent plasticity (STDP)

→ Timing between presynaptic & postsynaptic spikes.

Hebbian STDP :-

Presynaptic spike occurs before
postsynaptic spike → strengthened.

post occurs before pre → decreased

Afferent (Incoming):
Efferent (Outgoing)
CNS = Brain + Spinal cord

Hypothalamus - Fighting, Fleeing, Feeding
thalamus - Relay station for sensory
info to cortex

→ Cerebral cortex, gangalia, hippocampus,
amygdala. - perception, cognitive
f^n, emotion, memory, learning.

Prefrontal cortex - problem solving, emotion,
complex thought.

=

Cyber Bullying

3/12/22

4/2/22 EEG based BCI paradigms

ERD	Spontaneous
P300	Evoked
VEP/SSEP/AEP	Evoked
SCP	Spontaneous

P300 :- Positive curve EEG after 300ms.
→ Involved in Stimulus evaluation or categorization.

12/2/22
512 Hz, 512 samples recorded in one second.

Epoch - Represent data that is time-locked to repeated exper- events

→ Single trial EEG → Epochs → Training & Testing data

⇒ Cognitive Workload (CWL) is a demand placed upon humans for mental resources while performing a task n - Back Task :

sound - 2 Back

n times back , we must check the
→ current one with it . to match
→ Memorization & Focus is required

Position 2-back

→ Determine the position of block in
a 3×3 grid 2 times back

Frequency domain signals

→ EEG signals are recorded in time
domain.

→ Co-ordinate transform system
→ Introduced by Joseph Fourier in
early 1800's
→ Sine & cosine f^ns provide an
orthogonal basis for space of
solution f^ns

Sum of increasing freq.. of sine & cosine,
we are trying to approximate

* $f(x)$. infinite sum of sine & cosine

$$f(x) = \sum_{k=1}^{\infty} \left[A_k \cos(kx) + B_k \sin(kx) \right] + \frac{A_0}{2}$$

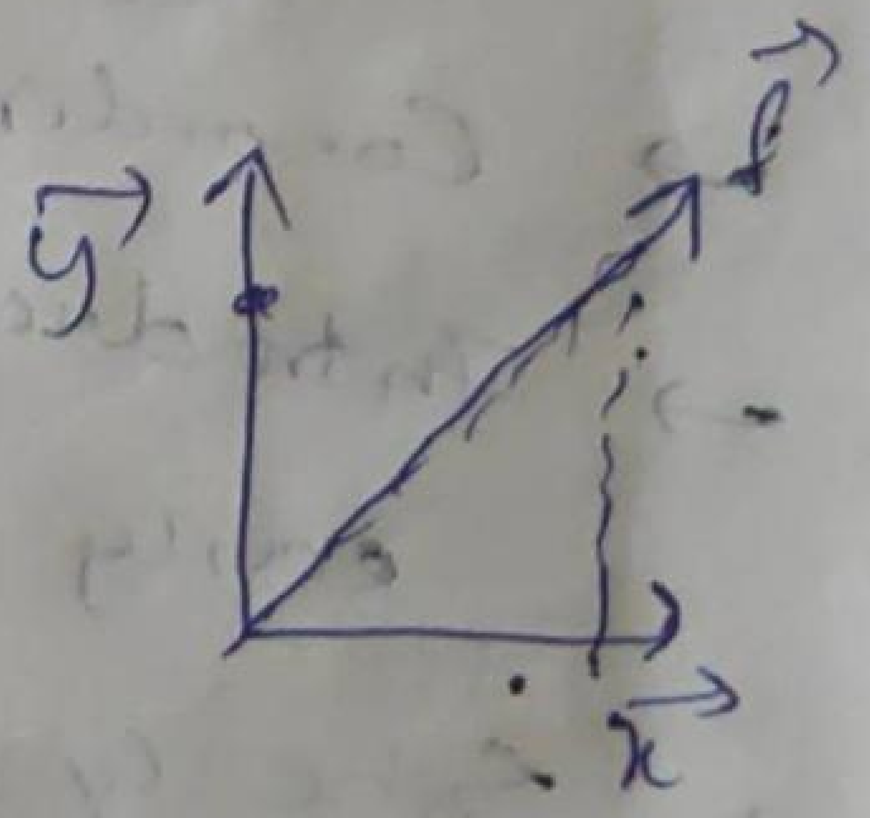
A_k, B_k are fourier constants.

$$A_k = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \cos(kx)\, dx$$

$$B_k = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \sin(kx)\, dx$$

$$A_k = \frac{1}{\|\cos(kx)\|^2} \langle f(x), \cos(kx) \rangle$$

$$\vec{f} = \langle \vec{f}, \vec{x} \rangle \cdot \frac{\vec{x}}{\|x\|^2} + \langle \vec{f}, \vec{y} \rangle \frac{\vec{y}}{\|y\|^2}$$

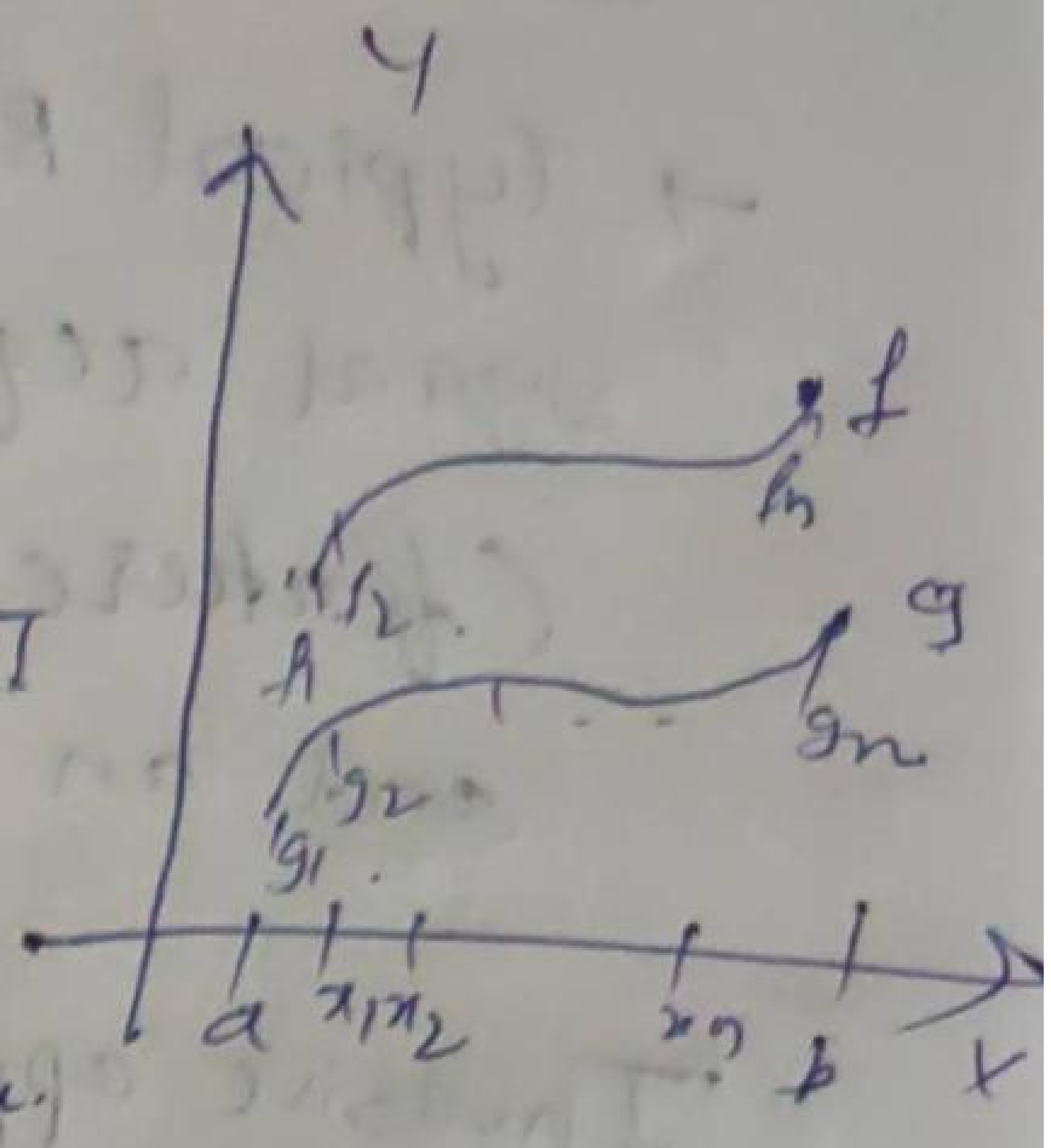


$$f(x) = f(x) \cos(kx) \left(\frac{\cos kx}{\|\cos kx\|} \right) + f(x) \sin(kx) \frac{\sin(kx)}{\|\sin kx\|}$$

↳ in f^n space

// 17/2/22

Inner product of f^n's



$f = [f_1, f_2, \ldots f_n]^T$

$g = [g_1, g_2, \ldots g_n]^T$

$$\langle f(x), g(x) \rangle = \int_a^b f(x) g(x)\, dx$$

where 'n' data points are increasing

$$\frac{b-a}{n-1} \langle f, g \rangle = \sum_{k=1}^{n} f(x_k) g(x_k) \, \Delta x$$

$n \to \infty \equiv \Delta x \to 0$

$$\Delta x = \frac{b-a}{n-1}$$

Fourier series for complex f^n's

$$f(x) = \sum_{k=-\infty}^{\infty} c_k e^{ik} \quad \left[e^{ik} = \cos kx + i \sin kx \quad \text{Euler exp}^n \right]$$

$$c_k = \alpha_k + i \beta_k$$

$$f(x) = \sum_{k=-\infty}^{\infty} (\alpha_k + i \beta_k) [\cos kx + i \sin(kx)]$$

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→ Typical BCI System comprises of signal acquistion, Signal processing (feature extraction & classification) and an output device.

Invasive approaches :-

→ Micro electrodes
→ Intracellular Recording
→ Extracellular Recording
→ Tetrodes / Multi-Unit Recording
→ Multielectrode Arrays

Partially Invasive

→ Electrocorticography (ECoG)
→ Micro ECoG
→ Optical Recording : Voltage - Sensitive Dyes
→ Two photon calcium imaging
→ Electro encephalography (EEG)

10-20 Standard
→ Magneto encephalography (MEG)
→ fMRI

, (FNIR)

{PET}:

→ CSPECT)

18/2/22

$$F\left(\frac{d}{dx}(f(x))\right) = \int_{-\infty}^{\infty} \frac{df}{dx} e^{-i\omega x} dx$$

$$= \left[f(x) e^{\frac{dv}{-i\omega x}} \right]_{-\infty}^{\infty} - \int_{-\infty}^{\infty} f(x) (-i\omega e^{-i\omega x}) dx$$

$$= 0 + i\omega \underbrace{\int_{-\infty}^{\infty} f(x) e^{-i\omega x} dx}_{F(f(x))}$$

F fourier transform

$$F\left(\frac{d}{dx}(f(x))\right) = i\omega F(f(x))$$

(2). Simplifying convolution Integral!

$$f * g = \int_{-\infty}^{\infty} f(x - \varphi) g(\varphi) d\varphi$$

$$F(f * g) = F(f) . F(g) = \hat{f} . \hat{g}.$$

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$$F^{-1}(\hat{f}\hat{g}) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{f}(\omega)\, \hat{g}(\omega)\, e^{i\omega x}\, d\omega$$

$$F^{-1}(\hat{f}\hat{g}) = \int_{-\infty}^{\infty} g(y)\, f(x-y)\, dy = \hat{f}.\hat{g}.$$

24/2/22

25/2/22

High pass filters :- Blocks dc offset in high gain amplifiers [only passes high filters]

Low pass filter :-

Band pass filter :- Combined / Cascaded of high-pass & low-pass.

→ passes frequencies of lower cutoff freq f_L, and upper cutoff frequency f_h.

: Notch (Band Reject filter)

→ Stops $f_L \to f_h$ [stop band] frequencies.

· Time Domain Analysis :-

[1970's]

(1) Hjorth parameters

→ Mean Power

→ RMS freq

→ RMS freq spread.

(2) Auto Regression

(3) Bayesian Filtering :-

28/2/22

$\Sigma_x u_i = \lambda_i u_i$

Step 1:- Compute sample mean $\bar{x} = \frac{1}{N}\sum_{i=1}^{M}$

Step 2:- Subtract x_i to $\bar{x}$

Step 3:- Calculate co-variance (sample)

Step 4:- compute eigenvalues/ eigenvectors of Σ_x.

17/3/22

Linear Regression:-

$$\min \sum_{i=1}^{m} (y_i - \hat{y}_i)^2 = \sum_{i=1}^{m} (y_i - (\hat{w} x_i + \hat{b}))^2$$

To minimize overfitting

- LASSO $\min \sum_{i=1}^{m} (y_i - w \cdot x_i - b)^2 + C \sum_{j=1}^{n} |w_j|$

- Ridge $\min \sum_{j=1}^{m} (y_i - w x_i - b)^2 + C \sum_{j=1}^{m} |w_j^2|$

SVR

Linear case :- $y_i = w_i x_i + b$

Non-linear :- $y_i = w\sqrt{x_i} + w_2\sqrt{2x_i^2} + b$

Update rules :- Delta Rule, Gradient, LMS

→ Guaranteed to converge to best fit [global min of E]

→ MLP with Back propagation for Non-linear Regression

= 17/3/22

Non-linear SVM's

→ we have a new dimension.

→ Map to some high-dimensional space to separate the data points

Why use Kernels :-

– Make non-seperable problem seperable

– Map data into better representational space

19/3/22

→ System which translates thoughts
↳ provides an interface used for
communication → BCI.

21/3/22

Motivation ⊢

→ Potential for re-storing lost sensory ↳
motor fn.

BCI ⊢ A system which translates thoughts
↳ provides an interface for communication.

[Signal Acquisition, Signal Processing, Output device].

BCI Applications ⊢

→ Communication
→ Automatic Motion controlling.
→ Device control.
→ Attention Monitoring.

Signal Acquistion →pre-processing→ Feature Extraction
→ Classification → Control signal → Application
→ Feedback

BCI Applications :-

→ Device control
→ User state monitoring.
→ Training & Education
→ Games & Entertainment.
→ Cognitive Improvement
→ Safety & Security.

Brain Activity :- (EEG, FNIRS, MEG)

Challenges :-

→ Usability
→ Hardware
→ Signal proccessing
→ System Integration
→ Cost

Central Nervous System (CNS)
Peripheral Nervous System (PNS) → Somatic NS, Autonomic NS

Sensory neurons → Interneurons → Motor neuron

$[Na^+], [Cl^-], [Ca^{+2}]$ → higher outside
$[K^+], [A^-]$ Anions → higher inside

Axons contains myelin   Synapses [chemically gated]

Excitatory synapses - Increase - Depolar
Inhibitory synapses - Decrease - Hyper pol

IONIC CHANNELS

- voltage gated
- chemically gated
- Mechanically gated

LTP (Long Term Potentiation)*

→ Increase in the synaptic strength of a synaptic connection between two neurons caused by correlated firing of 2 neurons

→ Measured as increase in EPSP.

LTD (Long Term - Depression) ↗ Reverse

STDP (Spike Timing Dependent plasticity)

→ Timing between presynaptic & postsynaptic spikes.

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PNS :-

→ Somatic / Skeletal Nervous System
→ Nerves that are connected to skeletal muscles & sensory receptors.

→ Autonomic NS :-
→ Connected to heart, blood vessels, smooth vessels, glands

22/3/22.

→ Invasive approaches :-
Techniques that involve recording of ~~signal~~ individual neurons.

1) Microelectrodes. - Simply thin wire.
2) Intracellular Recording - Measures voltage across membrane of brain tissue
3) Extracellular Recording.
- Recording of a single neuron at brain target area.

4) Tetrodes & Multi-unit Recordings :-
Four wires, multiple neurons.

5) Multi-electrode arrays :-
Larger number of neurons

Synaptic plasticity :-

→ Short term Falicitation :-

Effect of successive spike is greater than predecessor

→ Short term Depression

Hebbian STDP :-

Presynaptic spike occurs before postsynaptic spike → Synapse strength ↑.

Presynaptic spike occurs after post - spike → synapse strength ↓

Partially Invasive Approaches :-

1) Electrocorticography (ECOG) :-

→ Placing electrodes on surface of the brain

2) Micro ECOG :-

Micro electrodes [fraction of mm in diameter] placed 2-3 mm apart in a grid]

3) optical Recording :- [voltage sensitive-dyes & Two photon calcium Imaging]

→ neurons are Stained with voltage-dye

→ change in membrane potential is responded by flouroscence

Non-invasive approaches :

1.) Electroencephalography (EEG)

Summation of post synaptic potentials of thousands of neurons

→ Measured at cerebral cortex.

→ 10-20 system specify standardized electrode locations on scalp.

→ EEG Electrode one input → differential amplifier
other input - reference electrode

Amplified → Filter → A/D → Bandpass filter [1-50Hz]

Am decreases ←
Gamma → freq dec

EEG measures
→ Brain waves (BATD).

2) Magneto enceephalography (MEG):-

Measures the magnetic activity of thousands of cortical neurons

3) fMRI (functional Magnetic Resonance Imaging)

4) FNIR

→ Neurotransmitters to ligand-gated ion Channels

EEG measures
- volume conduction
- Neural activity
↓
[Action potentials, Postsynaptic pot]

- Differences in electric potential at scalp.

EEG is Non-invasive, covers whole head, very high temporal resolution

→ Neurons must give rise to a net dipole ~~mome~~ current

Hans Berger (1929) - EEG

Nasion | Frontal | Central | ~~perital~~ Parietal | ocippital | Inion

Frontal

Auricular Tem Central Tem Auricular

Parietal

Occipital.

A - G, R - G

Ground → voltages are measured
↓
Diff between partcip of amplifier.

Active

3 Ground

Reference.

→ Measuring EEG :-

EEG Records potential diff at scalp by using a set of electrodes.

Bipolar: [Between adjacent electrodes]
Unipolar [Between electrode of designated reference]

10-20

EEG Paradigms.

ERP (Event Related Potential)
→ Measured brain response that is result of thought or perception.

Categorisation of EEG Based B/I paradigms

→ Evoked (Subject attention is req)
→ Spontaneous (No continuous attention is req.

ERD/ERS Spont
P300 Evoked
SSEP/AEP/VEP Evoked

SCP Spont

ERP
↳ Averaging of trials following a stimulus.

- VEP (Visual Evoked potential)
- SSVEP (Steady-State - - -)

P300 ↳ 95% accuracy at 1 char per 26 sec.

ERS / ERD > P300 > SSVEP

Time Taken to train

EEG waveform [Montage]
representation
→ Sequential montage
→ Referential montage

EEG variables ↳

Frequency - Rhythmic repetitive activity { Rytm, Arryth, Dsyryth
Voltage — Avg voltage or peak
morphology → Shape of waveform

EEG Rhythms :-

Gam BAT D

>30 | 16-30 | 8-15 | 4-7 | <4

Fourier introduced the concept that sine & cosine f^ns forms the ~~basis~~ orthogonal basis of sol^n f^ns.

Arbitrary f^n

$$f(x) = \frac{A_0}{2} + \sum_{0}^{\infty} A_k \cos(kx) + B_k \sin(kx)$$

DFT? FFT?

wavelet trans

$$A_k = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \cos(kx)\, dx$$

$$B_k = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \sin(kx)\, dx$$

Fourier series for complex f^n

$$f(x) = \sum_{k=-\infty}^{\infty} C_k e^{ikx}$$

~~Spatial Filtering~~

~~Laplacian~~

Filtering :-

→ Spatial Filtering.

→ Bipolar.

→ Laplacian

→ Common average Reference

PCA :- Underlying statistical variability in data.

→ Reduce the data dimensionality [max variance]

PCA Steps :-

1) Compute sample mean
2) Subtract sample mean [Center data at 0]
3) Compute sample covariance matrix
4) Compute eigenvalues / eigenvectors of Σ
5) Dimensionality Reduction step
[approximate x using first k eigen vectors]

• [Finding directions of max variance in D-dim data]

Normalization
zero mean
Unit stand deviation

Decorrelation

Correleated multivariate distribution

↓

orthogonal linear combinations of original variables

PCA Reconstruction :-

PCA Re– = PC Scores · Eigenvectors^T + Mean

Common special pattern :

→ Can significantly enhance discrimination ability between two classes.

Artifacts Reduction :

→ thresholding

→ Band-stop & notch Filters

→ linear modelling.

29/3/22

3 girls

_ _ _ _ _

31/3/22

Nervous system

- CNS
- PNS
  - Somatic (Muscle nerves)
  - Autonomic (inside) (motor mov)
    - Sympatic (Flight)
    - Parasympathetic (Rest & Digest)

Autonomic Dysreflexia :- [AD]

→ Occurs in a person with Spinal cord injury.

→ Change in heart rate (Low)
Excessive Sweating.
High blood pressure.

→ Life Threathening Condn

—

Detecting it :-

→ Continuous monitoring of blood pressure/ heart rate through a device
[Cuff-based pressure monitor]

→ Band [Measures Skin Temp, Resistance, Heart Rate]

Alerts to mobile ← Remote server ← Band

Feedback

M.BATG

→ Machine Learning.

Features → ML Model → Classification
ST, SR, HR

→

SKNA [Skin Nerve Activity]

Rat ——— Ground Truth ———→ [ ]

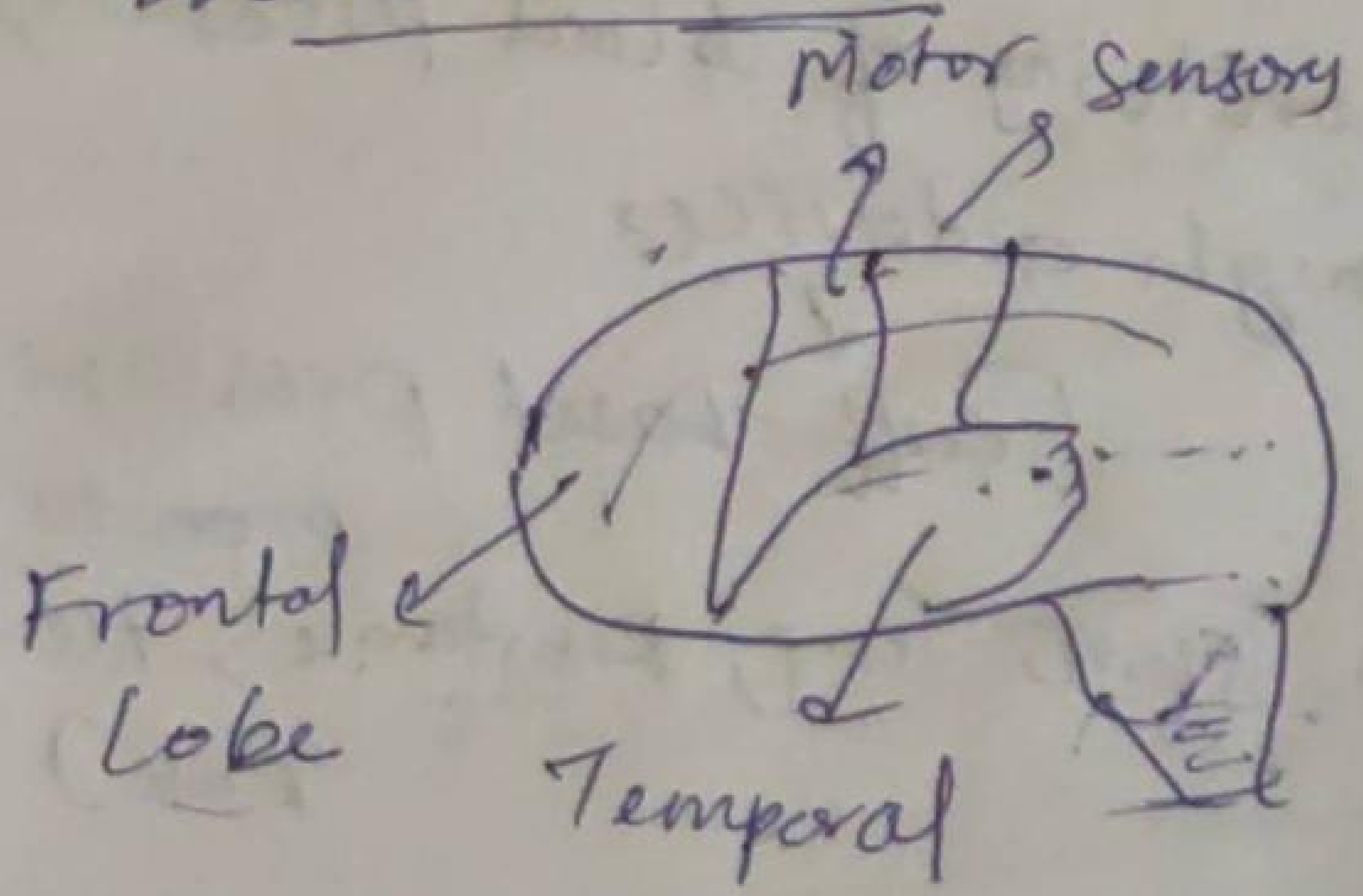
↓

SKNA

↓

WPD Features → [ ] → LSTM → [ ]

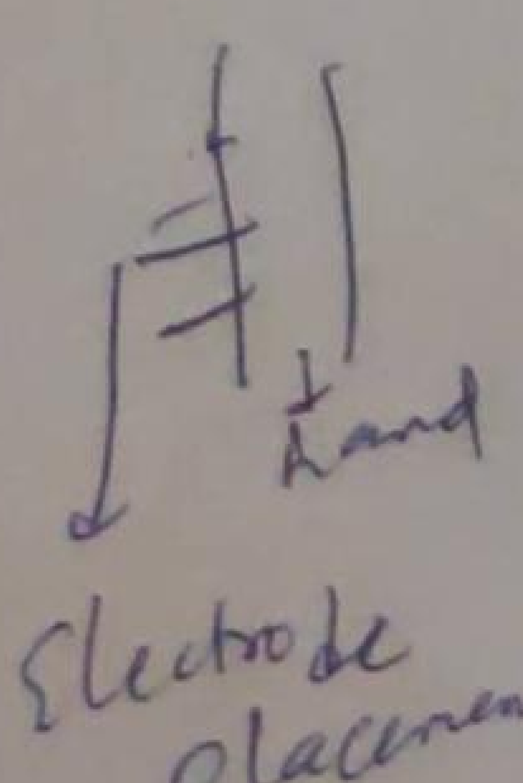
Brain Anatomy.



EMG signal formation :-

→ Several MUAP (motor unit action potential) are measured

→ Upper limb Prosthesis control based on EMG-PR



→ EMG Signal → Pre-process — EMG Features — Multi-out Classif — Digit action comds

— Action control.

HD (High Density) - EMG.

Array 1 - forearm
Array 2 - Biceps
Array 3 - Triceps

} multi-array EMG positions

NinaPro Database

Acclimate — stabilization. [2-weeks]

31/3/22

Neural Nets

Feature values

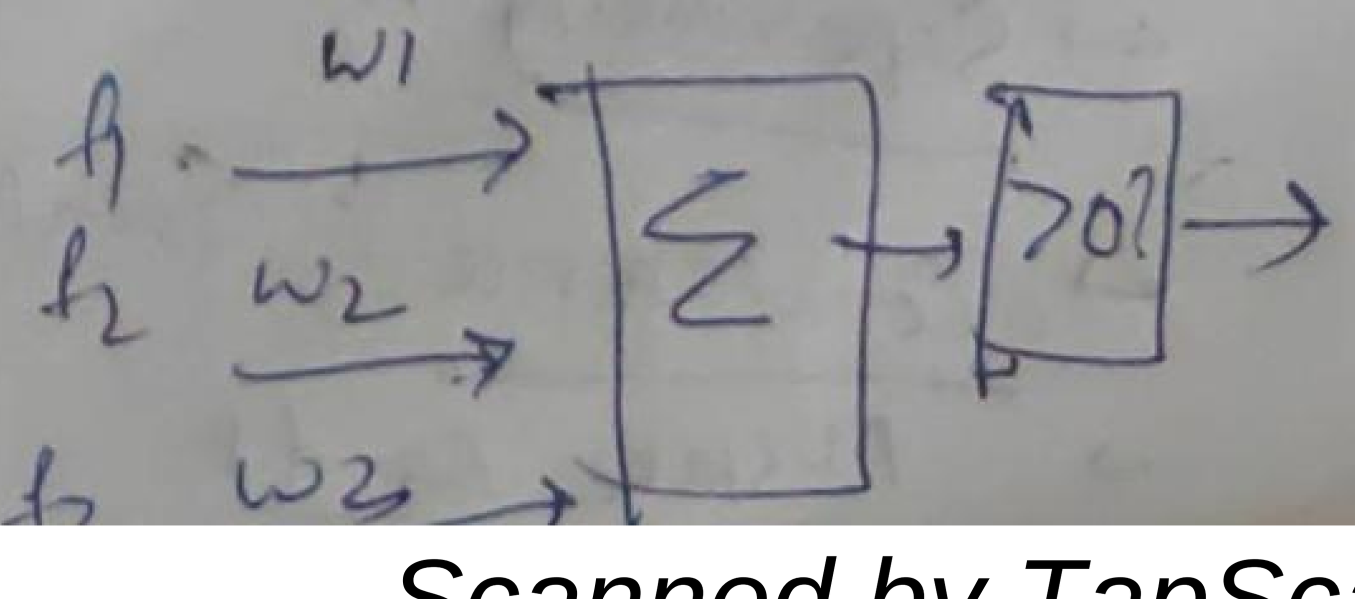
x $\longrightarrow$ f(x) $\rightarrow$ y.
Spam or not

M-Nist

Linear Classifier

→ Inputs are Feature values
→ Each feature has a weight
→ Sum is activation.

$$\text{activation}_w(x) = \sum_i w_i f_i(x) = w \cdot f(x)$$



Binary Decision Rule :

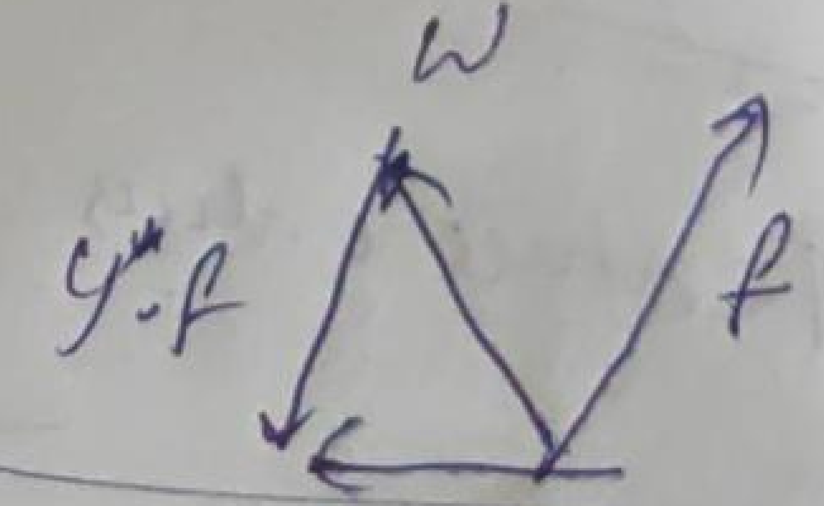
+1 → SPAM
−1 → HAM

→ Starts with weights = 0.
→ For each training instance :
  • Classify with current weights
→ if correct → no change!
  if wrong : adjust the weight vector.

$$y = \begin{cases} +1 & \text{if } w \cdot f(x) \geq 0 \\ -1 & \text{if } w \cdot f(x) < 0 \end{cases}$$

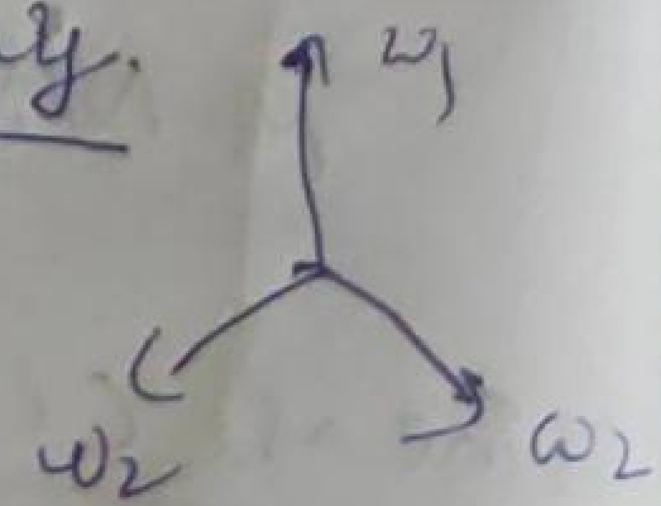
$$\underset{\text{new}}{w} = \underset{\text{old}}{w} + \underset{\text{output}}{y^*} \cdot \underset{\text{functional\_values}}{f}$$

Perceptron



Multiclass Decision Rule :

• A weight vector for each class w_y.



→ $w_y f(x)$
→ $y \to \arg_y \max w_y f(x)$

→ Pick up training examples one by one.

Properties of perceptrons :

→ Seperability : True if some parameters get training set perfectly correct.
→ Convergence : Eventually convergence, if seperable
→ Mistake Bound :

Problems :-

→ Noise :-

→ mediocre generalization :

→ overtraining :-

For non-seperable cases, use deterministic decision [probabilistic]

For probabilistic fns :-

$z = w \cdot f(x)$.

Perceptron scoring :-

Best w :- MLE (Maximum Likelihood Estimate)

$\Rightarrow \max_w ll(w) = \max_w \sum_i \log P(y^{(i)} / x^{(i)}; w)$

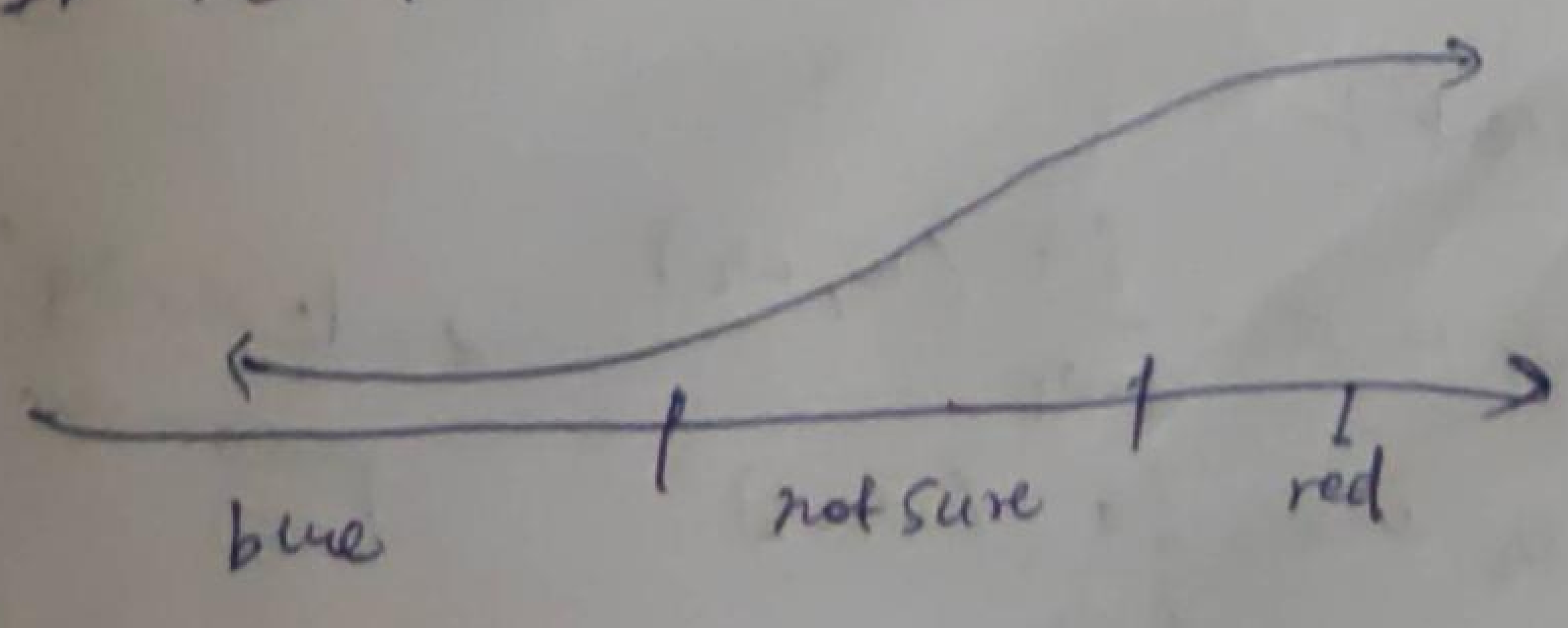
$P(y^{(i)} = +1 \mid x^{(i)}; w) = \dfrac{1}{1 + e^{-w \cdot f(x^{(i)})}}$.

$-1 = 1 - \ldots$

↓

Logistic Reg for single class

1D example.



curve values
more - red
less - blue

$$P(red/x) = \frac{e^{w_{red} \cdot x}}{e^{w_{red} \cdot x} + e^{w_{blue} \cdot x}}$$

$$P(y^{(i)} / x^{(i)}; w) = \frac{e^{w_{y(i)} \cdot f(x^{(i)})}}{\sum_y e^{w_y \cdot f(x^{(i)})}}$$

Soft Max.

Multi-class logistic Regression

1/4/22

Hello! Hill Climbing :-

- Start wherever
- Repeat :- move to best neighbouring state
- If no neighbors are better than current, quit

Could evaluate $g(w_0+h)$ and $g(w_0-h)$

$$\rightarrow \frac{\delta g(w_0)}{\delta w} = \lim_{h \to 0} \frac{g(w_0+h) - g(w_0-h)}{2h}$$

Gradient Ascent :-

$$w_1 \leftarrow w_1 + \alpha \cdot \frac{\delta g}{\delta w_1}(w_1, w_2)$$

$$w_2 \leftarrow w_2 + \alpha \cdot \frac{\delta g}{\delta w_2}(w_1, w_2)$$

α = learning parameter

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$\nabla_w g(w)$ $\quad\quad$ $\nabla_w g(w) = \begin{bmatrix} \frac{\delta g}{\delta w_1}(w) \\ \frac{\delta g}{\delta w_2}(w) \end{bmatrix}$ = Gradient

$$\boxed{w \leftarrow w + \alpha \cdot \nabla_w g(w)}$$

$\Rightarrow$ $\max\limits_{\Delta : \Delta_1^2 + \Delta_2^2 \le \varepsilon} \quad g(w+\Delta)$

$$g(w+\Delta) = g(w) + \frac{\delta g}{\delta w_1}\Delta_1 + \frac{\delta g}{\delta w_2}\Delta_2$$

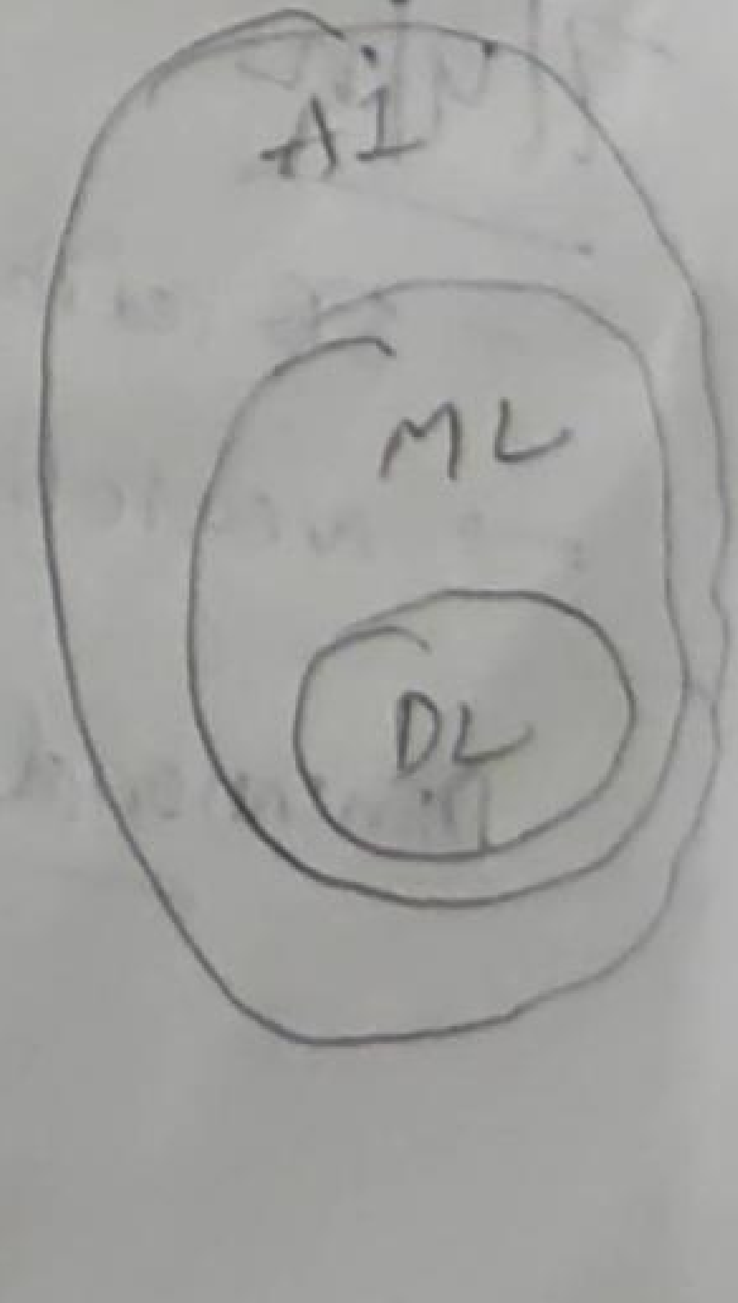
Taylor Expansion
(First-order)

= max of

Steepest direction

Recall : $\max\limits_{\Delta : \|\Delta\| \le \varepsilon} \Delta^T a \rightarrow \Delta = \frac{a}{\|a\|}$

Solution : $\Delta = \varepsilon \frac{\nabla g}{\|\nabla g\|}$



- → Batch gradient descent
- → Stochastic
- → Mini-batch.

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→ just run gradient descent. (Training Dem)
+ stop when log likelihood of hold-out data
starts to decrease.

Hornik Universal Approximation Theorem :

→ ~~Calculus~~

[1 Question in end on problem derivatives]

→ Training Neural networks.
- Forward.
- Backward.
- Gradient.
- Backprop.

[Back prop Q in exam prob]

$$\nabla g = \left[\frac{dg}{dw_1}, \frac{dg}{dw_2}\right] = [39, 8].$$

neuro science...

7/4/22

- FB reality labs
→ Neuralink

David Schimmer

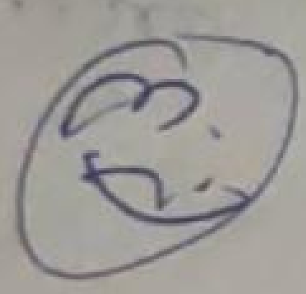
Dimensionality Reduction + Manifold learning.

$ 7/9/21 Assignment

Pattern analysis indicate central motor ~~origin~~ areas as origin of discr— signals

68.4% [Proof-of-concept to classify movement attempts online in a closed loop]

Palmar grasp



Sensorimotor cortex

→ Comprises of precentral & post central gyri, cores primary sensory & motor areas of brain

Movement related cortical potentials (MRCP's)

MRCP's encode info about hand & limb m

pronated - leaning inward foot

Supinated - leaning outward foot

multi-class
Shrinkage linear Discriminant Analysis
(SLDA) classifier

- 45.3% at 1.1 sec

Proof of concept →

→ To, demonstrate the classification of hand open vs palmar grasp in a closed loop. for a participant with SCI.

low frequency time domain signals (MRCP's)

↳ Decoding hand & arm movements from persons with cervical SCI..

Training

movement, rest

→ false positive

True positive

Classification accuracy calculated to the center of feature extraction window

11/4/22

Performanse Evaluation :- [skimming]

1. Holdout Method.
2. Random subsampling.
3. Cross-validation.
4. Boots trap approach.

Accuracy :-

→ True ~~Accuracy~~ Accuracy :- ~~Traning~~ Testing the classifier with all possible unseen data

→ Predictive Accuracy :- Testing with just the test dataset.

Performance Estimation :-

→ Accuracy can't be used for imbalanced classy.

	+ T	− F
+	TP	FN
−	FP	TN

	+	−ve
T	~~TF~~	TN
F	FP	~~FN~~

Recall, sensititity, → TPR → $\frac{TP}{TP+FN}$

Precision = $\frac{TP}{TP+FP}$

Ultra-liberal

	+	-
+	P	0
-	N	0

Ultra-Conservative

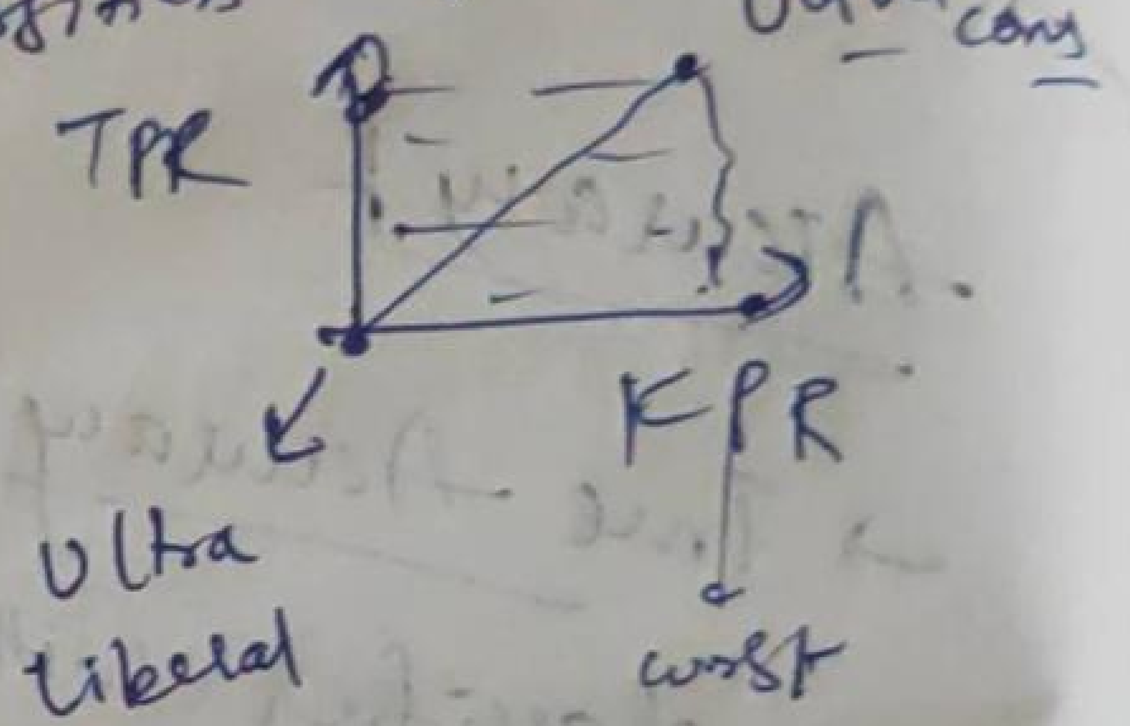
0	P
0	N

RoC curve :-

→ Receiver operating characteristic

→ To compare two classifiers

→ Take Area under curve for best classifier.



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Features :-

→ Detect & quantify characteristics of brain signals

Brain Signals → Amplifier → Digitize → Spatial filtering

↓

Overlapping of blocks → Feature extraction & conditi → Feature vector → Feature Transla

→ Application Device → User Feedback → Brain Signals

Linear / Nonlinear comb }
Ratios } · Most features should be.
statistical measures
transformation of fundamental features.

Spatial filtering, focus on determining the intensity of a pixel according to intensity of neighbouring pixels.

Feature vector

→ Spatial, temporal, spectral analysis must be able to characterize for an user or population of users.

→ Features can be modulated according to user's intent, combined with other features.

→ Co-relation with user's intent & feature vector is stable over time.

$$P(M = Yes \mid C = Yes) = \frac{P(M = Yes \,\&\, C = Yes)}{P(class = Yes)} = \frac{6}{9 \cdot 3}$$

$X(\omega) = a(\omega) + jb(\omega)$

$a(\omega) = \int_{-\infty}^{\infty} x(t)\cos\omega t\,dt$

$b(\omega) = \int_{-\infty}^{\infty} x(t)\sin\omega t\,dt$

= (3) steps

(1) Signal conditioning to reduce noise & enhance relevant aspects of signals

(1)

→ Frequency-range - prefiltering

= Data dependendent spatial filtering (PCA, ICA, CSP)

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D T A B G — 30-100

0.1-4, 4-8, 8-13, 13-30

D - sleep — ever

T - Frustation — temporal & parietal | sleep

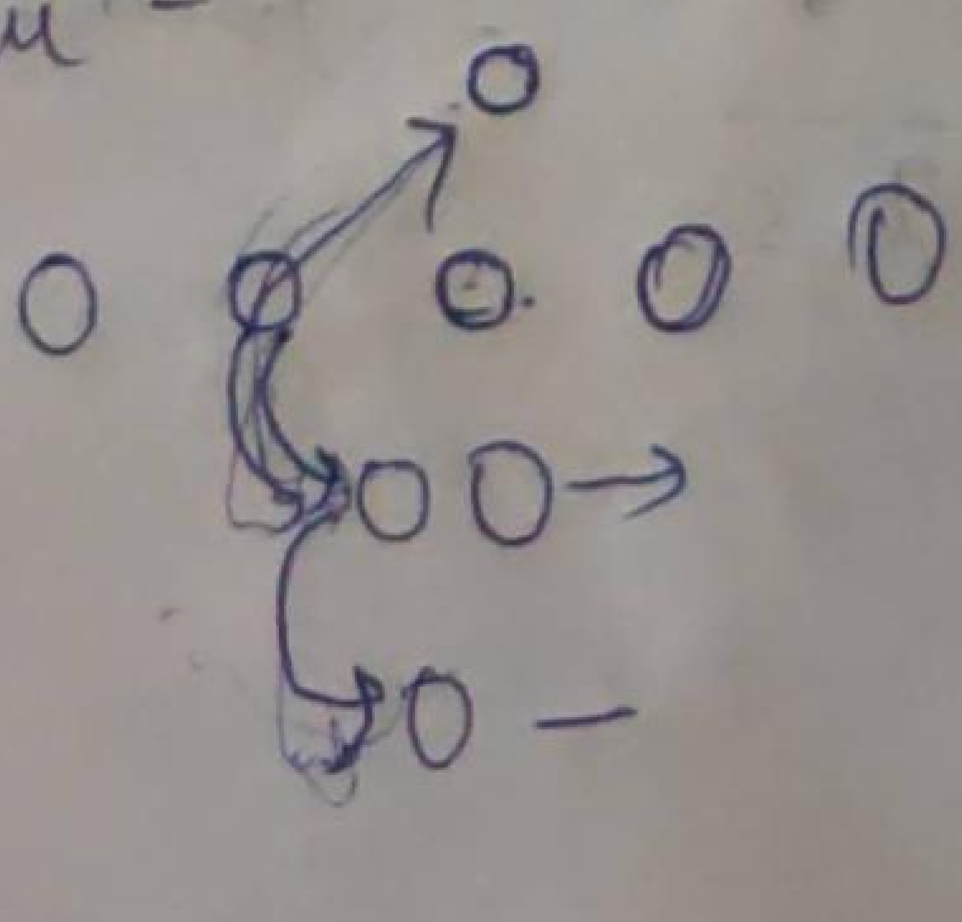
A - mental imaginery — occipital & parietal

B - mental activity - parietal & frontal

G - cognitive decline - Somatosensory cortex

Mu - Intention of movement

hit rate :



Representation of waveform — montage

Morphology — shape of waveform

Seq

Repor

ERP

VEP
AEP
SSVEP
P300
ERS/ERD
SCP

Cluster

k-means

Decision Tree

KNN

		C_1	C_2	C_3
6.8	12.6	4.03	4.01	6
0.8	9.8	3.001		
1.2	11.6			
2.8	9.6			
3.8	9.9			
4.4	6.5			
4.8	1.1			
6.0	19.9			
6.2	18.1	C_3		
7.8	12.2	C_2		

Estimation strategies

Accuracy → true / predictive

class imbalance

confus matrix

Pred Acc

Performance

		Predict +	Predict −
Actual	+	TP	FN
	−	FP	TN

$TPR = \frac{TP}{TP+FN}$

Recall, Sens, Hit Rate

TNR = specificity

$\frac{TP}{TP+FP}$ → Precision

Ultra-liberal → +ve

Ultra-conser → −ve

TPR

FPR

$f(x) = \frac{A_0}{2} + \sum_{k=1}^{\infty} [A_k \cos(kx) + B_k \cos^{kx}_{\sin})$

$A_k = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \cos(kx)\, dx$

$A_0 = \frac{1}{L} \int_{-\pi}^{\pi} f(x)\, dx$

Feature condit

✓ Normalization

✓ log-normal Transforms

✓ Feature Smoothing

✓ PCA & ICA

$$y = a + bx$$

$$b = \frac{\Sigma (x_i - \bar{x})(y_i - \bar{y})}{\Sigma (x_i - \bar{x})^2}$$

$$a = \bar{y} - b\bar{x}$$

$$SSE = (y_i - \hat{y})^2$$

$$SST = (y_i - \bar{y})^2$$

$$\tilde{R} = 1 - \frac{SSE}{SST}$$

→ Mutually exclusive & exha

→ Attributes are independent